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THE αβ FILTER IN DRAG WITH DATA ASSOCIATION

Roy L. Streit
Submarine Combat Systems Directorate

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The well-known alpha beta filter achieves its best performance when measurement outliers are rare. Two modifications of the alpha beta filter are presented for improving its performance when outliers are commonplace. The alpha beta mu filter uses a drag coefficient to ensure that the target motion model has a finite asymptotic velocity variance. Although the alpha beta filter mu is less sensitive to outliers than the alpha beta filter, it does not directly address the problem of large spurious measurements. The alpha beta mu sigma filter is a probabilistically based, nonlinear target estimation filter that is much more robust against outliers than the alpha beta filter. To facilitate understanding of the filter optimization problem and to enable computation of filter outputs crucial to the post-processing task of associating collections of tracking filters, it is recommended that the alpha beta filter, together with all the important earlier work that has made it useful in applications, be reinterpreted in the Kalman filter paradigm.

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ABSTRACT

The well-known $\alpha\beta$ filter achieves its best performance when measurement outliers are rare. Two modifications of the $\alpha\beta$ filter are presented for improving its performance when outliers are commonplace. The $\alpha\beta\mu$ filter uses a drag coefficient to ensure that the target motion model has a finite asymptotic velocity variance. Although the $\alpha\beta\mu$ filter is less sensitive to outliers than the $\alpha\beta$ filter, it does not directly address the problem of large spurious measurements. The $\alpha\beta\mu\sigma$ filter is a probabilistically based, nonlinear target estimation filter that is much more robust against outliers than the $\alpha\beta$ filter. To facilitate understanding of the filter optimization problem and to enable computation of filter outputs crucial to the post-processing task of associating collections of tracking filters, it is recommended that the $\alpha\beta$ filter, together with all the important earlier work that has made it useful in applications, be reinterpreted in the Kalman filter paradigm.

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1. INTRODUCTION

The $\alpha\beta$ tracking filter for estimating target position and velocity from position measurements pre-dates the Kalman filter by several years; see, for example, the classic papers [1] and [2]. Implicit in its design is the assumption that measurement outliers are rarely encountered. While such an assumption may be appropriate at sufficiently high signal-to-noise ratio (SNR), it is clearly not appropriate when the SNR is low enough that outliers are commonplace. Tracking filters for low SNR targets must therefore be designed with some provision to accommodate measurement outliers. Two simple modifications of the $\alpha\beta$ filter are proposed here for improving its performance when measurement outliers are a frequent occurrence.

The first modification of the $\alpha\beta$ filter is the use of a drag coefficient, denoted by μ, to modulate the velocity in the prediction equation. The resulting tracker, called herein the $\alpha\beta\mu$ tracker, is less sensitive to outliers than the standard $\alpha\beta$ filter. It is discussed in Section 2. The $\alpha\beta\mu$ tracker reduces to the $\alpha\beta$ tracker when $\mu = 1$.

The second modification, discussed in Section 3, extends the $\alpha\beta\mu$ tracker to include a probabilistic data association (PDA) technique to estimate a weighted combined measurement innovation (called the "error" or "residual" in the usual language of the $\alpha\beta$ filter) to use in the position and velocity update equations. The resulting filter, called the $\alpha\beta\mu\sigma$ filter, is more robust to tracking in the presence of outliers than the standard $\alpha\beta$ filter; see [3] and [4] for examples.

It is recommended in Section 4 that the $\alpha\beta$ filter, together with the important developmental work that has made it useful in applications, be reinterpreted in a completely probabilistic paradigm such as that of the Kalman filter. A probabilistic theoretical foundation is necessary because it greatly facilitates understanding the parameter optimization problems of the $\alpha\beta$, $\alpha\beta\mu$, and $\alpha\beta\mu\sigma$ filters, and because it enables the computation of the statistically meaningful filter outputs essential to the task of correctly associating collections of tracks — a task performed in the post-processor downstream of the tracking filters.

2. THE αβ FILTER WITH VELOCITY DRAG

The discussion throughout is restricted to one dimensional position measurements, but extension to the general measurement case is conceptually straightforward. Let $\widehat{x}_{0|0}$ and $\widehat{v}_{0|0}$ be given initial estimates of target position and ve-

locity, and let T denote the interval between successive measurements. For $k = 1, 2, ...,$ the standard $\alpha\beta$ tracking filter prediction equations are given by

$$\begin{aligned} \widehat{x}_{k|k-1} &= \widehat{x}_{k-1|k-1} + T\ \widehat{v}_{k-1|k-1}, & (2.1) \\ \widehat{v}_{k|k-1} &= \widehat{v}_{k-1|k-1}\,. & (2.2) \end{aligned}$$

Let z_k denote the measured position at time kT. The $\alpha\beta$ filter estimation equations at time kT are given by

$$\begin{aligned} \widehat{x}_{k|k} &= \widehat{x}_{k|k-1} + \alpha_k (z_k - \widehat{x}_{k|k-1}), & (2.3) \\ \widehat{v}_{k|k} &= \widehat{v}_{k|k-1} + \frac{\beta_k}{T}(z_k - \widehat{x}_{k|k-1}), & (2.4) \end{aligned}$$

where the coefficients α_k and β_k are tracking system gains. These system gains are either given or computed adaptively using information that is statistically independent of target position and velocity, e.g., estimated SNR at time kT.

The $\alpha\beta\mu$ tracking filter is the $\alpha\beta$ filter modified by a drag coefficient in the velocity prediction equation (2.2). Specifically, it is assumed that

$$\widehat{v}_{k|k-1} = \mu\ \widehat{v}_{k-1|k-1}, \tag{2.5}$$

where μ is chosen so that $0 < \mu \leq 1$. The standard $\alpha\beta$ filter is the special case $\mu = 1$. The $\alpha\beta\mu$ filter was first proposed in [5]. (For a related discussion on exponential data weighting and asymptotic stability in a Kalman filter setting, see [6, Section 6.2]). The $\alpha\beta\mu$ filter is useful in situations where velocity estimates are biased high due to extraneous effects such as outliers (i.e., spurious measurements unrelated to the target). Drag coefficients $\mu < 1$ result in a finite asymptotic velocity variance with additive Gaussian errors, as is shown below, at the cost of introducing lag into the filter estimates.

The Gauss-Markov dynamical target velocity model implicit in (2.5) is

$$v_k = \mu\ v_{k-1} + T\ w_k, \tag{2.6}$$

where $\{w_k\}$ is a sequence of independent, identically distributed Gaussian random accelerations. Denote the variance of these random accelerations by σ^2_{acc}. The second moment of v_k is, using (2.6) and the independence of w_k and v_{k-1},

$$\begin{aligned} E[(v_k)^2] &= E[(\mu\ v_{k-1} + T\ w_k)^2] \\ &= \mu^2\ E[(v_{k-1})^2] + T^2\ \sigma^2_{acc}. & (2.7) \end{aligned}$$

It follows by induction from (2.7) that, for $k \geq 1$,

$$\begin{aligned} E[(v_k)^2] &= \mu^{2k}\, E[(v_0)^2] + T^2\sigma_{acc}^2 \sum_{j=0}^{k-1} \mu^{2j} \\ &= \mu^{2k}\, E[(v_0)^2] + T^2\sigma_{acc}^2 \left(\frac{1-\mu^{2k}}{1-\mu^2}\right). \end{aligned} \tag{2.8}$$

Similarly, $E[v_k] = \mu E[v_{k-1}]$, and $E[v_k] = \mu^k E[v_0]$. Squaring and subtracting from (2.8) gives the variance of v_k in terms of μ and the variance of v_0. Explicitly,

$$\begin{aligned} Var[v_k] &= E[(v_k)^2] - (E[v_k])^2 \\ &= \mu^{2k}\, Var[v_0] + T^2\sigma_{acc}^2 \left(\frac{1-\mu^{2k}}{1-\mu^2}\right). \end{aligned} \tag{2.9}$$

Taking the limit in (2.9) as $k \to \infty$ gives, since $\mu < 1$,

$$\sigma_{vel}^2 \equiv \lim_{k\to\infty} Var[v_k] = \frac{T^2\sigma_{acc}^2}{1-\mu^2}. \tag{2.10}$$

From (2.10) it is clear that $\sigma_{vel}^2 \to \infty$ as $\mu \to 1$; hence, the case $\mu = 1$ results in dynamical models that are physically unrealistic for targets of finite mass. Solving (2.10) for μ gives

$$\mu = \sqrt{1 - \left(\frac{T\sigma_{acc}}{\sigma_{vel}}\right)^2}. \tag{2.11}$$

The variance ratio $(T\sigma_{acc}/\sigma_{vel})^2$ is dimensionless.

If the asymptotic velocity variance σ_{vel}^2 is specified, the standard $\alpha\beta$ filter is recovered approximately for small random accelerations. Table 1 supports this statement numerically.

A more general analysis with nonstationary drag coefficients $\{\mu_k\}$ is potentially of interest, especially if μ_k is to be estimated adaptively as a function of target type or estimated SNR.

Table 1. Evaluation of Equation (2.11)

μ	$T\sigma_{acc}/\sigma_{vel}$
0.436	0.9
0.600	0.8
0.714	0.7
0.800	0.6
0.866	0.5
0.917	0.4
0.954	0.3
0.980	0.2
0.995	0.1

3. THE αβμ FILTER WITH PDA

The $\alpha\beta$ and $\alpha\beta\mu$ filters do not estimate a covariance matrix corresponding to their state estimates $(\widehat{x}_{k|k}, \widehat{v}_{k|k})$. They also do not require the specification of measurement covariances. These statistically significant oversights are easily rectified by reformulating the $\alpha\beta$ filters as Kalman filters; however, such reformulations lose some of the historically important computational economy of the original filter.

A more serious problem is that the $\alpha\beta$ filter performs poorly in environments that experience outliers. Rectifying this problem requires modifying the basic structure of the filter. The PDA technique is designed for tracking in the presence of outliers using the Kalman filter [7, Chapter 3]; however, the assumptions of the Kalman filter are unnecessarily restrictive. The proposed technique respects the computational economy of the original $\alpha\beta$ filter and avoids the Kalman filter formalism. Discussion and examples of the PDA $\alpha\beta$ filter are given in [3] and [4].

Measurements are typically generated in practice by thresholding a sensor output "image" comprising a finite number of pixels, or cells, to locate the output "peaks." Thresholds may be fixed or chosen adaptively to match the estimated background noise, and they may vary from cell to cell. Preprocessors typically refine these initial peaks in some way (e.g., beam interpolation) to improve estimates of their location, but the end result is conceptually unchanged — the estimated locations of sufficiently large (i.e., above threshold) local peaks of the

sensor output make up the measurement set used for tracking. Spurious local peaks (i.e., measurements) unrelated to the target are generated by noise at the sensor input, a problem that is greatly exacerbated when the target SNR is low. Consequently, all practical trackers must provide some mechanism for treating measurement outliers.

In the PDA Kalman filter, an innovation variance σ_{inn}^2 is updated during the prediction phase of the tracking filter. For the $\alpha\beta\mu\sigma$ filter, σ_{inn}^2 is assumed to be a known function of α, β, and μ and so is independent of k (unless α, β, and μ are estimated adaptively). The nominal validation gate is the interval

$$G = [\widehat{x}_{k|k-1} - g\sigma_{inn},\ \widehat{x}_{k|k-1} + g\sigma_{inn}],$$

where $g > 0$ is a specified constant called the normalized gate width parameter. In practice, however, the gate width must be adjusted slightly from scan to scan to accommodate the changing values of $\widehat{x}_{k|k-1}$ relative to the fixed cell structure of the sensor output. The exact validation gate is defined by the interval

$$G(k) = [\widehat{x}_{k|k-1} - g_k\sigma_{inn},\ \widehat{x}_{k|k-1} + g_k\sigma_{inn}], \tag{3.1}$$

where the normalized gate width parameter $g_k > 0$ is computed from $\widehat{x}_{k|k-1}$ and the sensor cell structure so that $g_k \approx g$. Let $m(k) \geq 1$ denote the number of measurements of target position at time kT, and let

$$\{z_k(1), z_k(2), ..., z_k(m(k))\} \tag{3.2}$$

denote the measurements themselves. Measurements lying outside the gate $G(k)$ are deleted; hence, it is assumed that all the measurements (3.2) lie within the gate $G(k)$. Let $\mathcal{N}(x; a, \sigma^2)$ denote the Gaussian density function with mean a and variance σ^2 evaluated at the point x, and let

$$P_{G(k)} = \int_{G(k)} \mathcal{N}(x; \widehat{x}_{k|k-1}, \sigma_{inn}^2)\, dx \tag{3.3}$$

denote the probability that a target measurement falls in the gate. Thus, $P_{G(k)} \to 1$ as $g_k \to \infty$. Let

$$\varepsilon_i = \exp\left\{-\frac{1}{2}\left[\frac{z_k(i) - \widehat{x}_{k|k-1}}{\sigma_{inn}}\right]^2\right\}, \qquad i = 1, ..., m(k), \tag{3.4}$$

$$\varepsilon_0 = \sqrt{\frac{\pi}{2}}\left(\frac{\overline{m(k)}_{G(k)}}{g_k}\right)\left(\frac{1 - P_D P_{G(k)}}{P_D}\right), \tag{3.5}$$

where P_D is the probability that a measurement of the target is in the measurement set (3.2), and $\overline{m(k)}_{G(k)}$ is the expected number of measurements that fall within the gate. Evaluating $\overline{m(k)}_{G(k)}$ requires a statistical model of outliers, which may not be available. Another approach is simply to put $\varepsilon_0 = m(k)$. In practice it is probably preferable to take ε_0 as a free design parameter that is either specified in advance or estimated adaptively.

Compute the conditional probabilities

$$\pi_i = \frac{\varepsilon_i}{\varepsilon_0 + \sum_{j=1}^{m(k)} \varepsilon_j}, \qquad i = 1, ..., m(k), \tag{3.6}$$

$$\pi_0 = \frac{\varepsilon_0}{\varepsilon_0 + \sum_{j=1}^{m(k)} \varepsilon_j}, \tag{3.7}$$

and compute the weighted combined innovation

$$\nu_k = \sum_{i=1}^{m(k)} \pi_i \left(z_k(i) - \widehat{x}_{k|k-1} \right). \tag{3.8}$$

The prediction equations of the $\alpha\beta\mu\sigma$ filter are

$$\widehat{x}_{k|k-1} = \widehat{x}_{k-1|k-1} + T\ \widehat{v}_{k-1|k-1}, \tag{3.9}$$

$$\widehat{v}_{k|k-1} = \mu\ \widehat{v}_{k-1|k-1}, \tag{3.10}$$

and the estimation equations of the $\alpha\beta\mu\sigma$ filter are

$$\widehat{x}_{k|k} = \widehat{x}_{k|k-1} + \alpha_k\ \nu_k, \tag{3.11}$$

$$\widehat{v}_{k|k} = \widehat{v}_{k|k-1} + \frac{\beta_k}{T}\ \nu_k. \tag{3.12}$$

The prediction equations (3.9)-(3.10) are identical to the $\alpha\beta\mu$ filter, and the estimation equations (3.11)-(3.12) are altered from those of the $\alpha\beta\mu$ filter by the use of a weighted innovation over the $m(k)$ measurements. The nonlinear innovation is crucial to the ability of the $\alpha\beta\mu\sigma$ filter to handle outliers.

An important special case is $m(k) \equiv 1$, $k = 1, 2, ...$, that is, when there is exactly one measurement at every time kT. From (3.6), (3.4) and (3.8), it follows that the weighted combined innovation is

$$\nu_k = \frac{z_k(1) - \widehat{x}_{k|k-1}}{1 + \varepsilon_0 \exp\left\{ +\frac{1}{2} \left[\frac{z_k(1) - \widehat{x}_{k|k-1}}{\sigma_{inn}} \right]^2 \right\}} \tag{3.13}$$

$$\equiv \kappa \left(z_k(1) - \widehat{x}_{k|k-1} \right), \tag{3.14}$$

where the innovation gain κ is, for general real values u,

$$\kappa = \kappa(u) = \frac{1}{1 + \varepsilon_0 \exp\left\{\frac{1}{2}\left[\frac{u}{\sigma_{inn}}\right]^2\right\}}. \tag{3.15}$$

It is evident from (3.13) that $\nu_k \to 0$ as the unweighted measurement innovation $z_k(1) - \widehat{x}_{k|k-1}$ goes to ∞. Thus, the $\alpha\beta\mu\sigma$ filter does not reduce to the $\alpha\beta\mu$ filter because of the possibility that the given measurement is an outlier and does not actually originate from the target. From (3.13) and (3.5), it also follows that the $\alpha\beta\mu\sigma$ filter reduces to the $\alpha\beta\mu$ filter when $m(k) = 1$ only if the product $P_D P_{G(k)} = 1$, that is, only in the limit as the gate width parameter $g \to \infty$ and $P_D = 1$. The result (3.13) is important in applications because it shows that less than the full measurement innovation should be used in the $\alpha\beta$ filter when there exists an element of doubt (e.g., $P_D < 1$) as to the correct origin of the measurement.

The general shape of the innovation gain, or weighting function, $\kappa(u)$ over the gate $G(k)$ is controlled by the parameters ε_0 and σ_{inn}. Let $a = \kappa(0)$ denote the peak value, and let $b = \kappa(g_k \sigma_{inn})$ denote the value at the edge of the gate. Clearly, $0 < a < 1$ and $0 < b < 1$. Using (3.15) and solving these two equations for ε_0 and the normalized gate width parameter g_k gives

$$\varepsilon_0 = \frac{1-a}{a}, \tag{3.16}$$

and

$$g_k = \sqrt{2 \ln\left(\frac{a}{1-a}\,\frac{1-b}{b}\right)}. \tag{3.17}$$

For example, for $a = 0.98$ and $b = 0.70$, equations (3.16) and (3.17) give

$$\varepsilon_0 = 0.02041 \text{ and } g_k = 2.468. \tag{3.18}$$

Figure 1 plots $\kappa(u)$ for this example for the special case $\sigma_{inn} = 1$.

The nonlinear Bayesian style ratios (3.6) - (3.7) are probably more significant than the exponential function in (3.4), so any similarly tapered function can be used without risking significant loss of performance. For example, the approximation

$$e^{-x^2/2} \approx \frac{1 - 0.075\ x^2}{1 + 0.625\ x^2}, \qquad |x| \leq 3.65148, \tag{3.19}$$

has an error of at most 0.0694307 and the right hand side is nonnegative on the specified interval; see Figures 2 and 3.

4. RECOMMENDATIONS

The $\alpha\beta$ filter is predicated on the assumption that the correct target measurement is known and is always correctly assigned to the filter. Given sufficiently many outliers or low enough SNR, such an assumption will lead to serious performance degradation. The greater the outlier density or the lower the SNR, the more often measurements unrelated to the target will enter the filter and cause it to lose track. Methods are widely available in the tracking literature (see, e.g., [7]) for dealing with outliers in a tracking filter; however, incorporating these advances into the $\alpha\beta$ filter requires switching to a completely probabilistic paradigm such as that of the Kalman filter.

It is recommended that the $\alpha\beta$ filter, together with all the important work that has gone into making it useful in applications, be reinterpreted in the Kalman filter paradigm. There are several reasons for this recommendation. Firstly, the switch to a probabilistic formulation greatly facilitates understanding tracking filter optimization. The important practical problem of selecting the best numerical values of the available design parameters (e.g., α, β, μ, and σ) becomes more difficult as the number of parameters increases. Secondly, a probabilistic formulation enables the computation of filter outputs (such as the error variance of the estimated track) that are vital to the task of associating multiple tracks — a task performed in the post-processor downstream of the tracking filters. Track association is a very important problem in many applications, and consistent statistical tracker outputs are essential to its solution. Finally, switching to a probabilistic formulation promotes informed technical peer review and enables advances in state-of-the-art tracking technology to be incorporated more quickly into current systems and applications.

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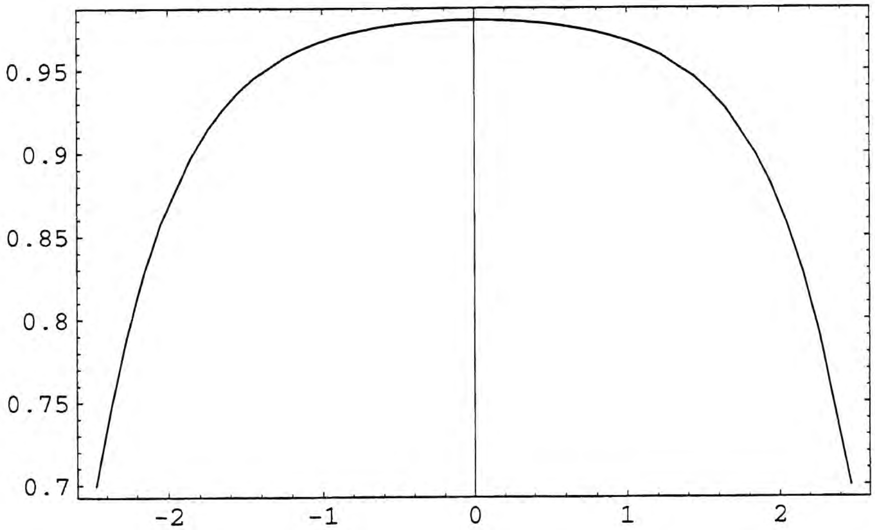

Figure 1. Innovation gain $\kappa(u)$ over the gate $G(k) = [-2.468,\ 2.468]$ for $a = 0.98$, $b = 0.70$, and $\sigma_{inn} = 1$.

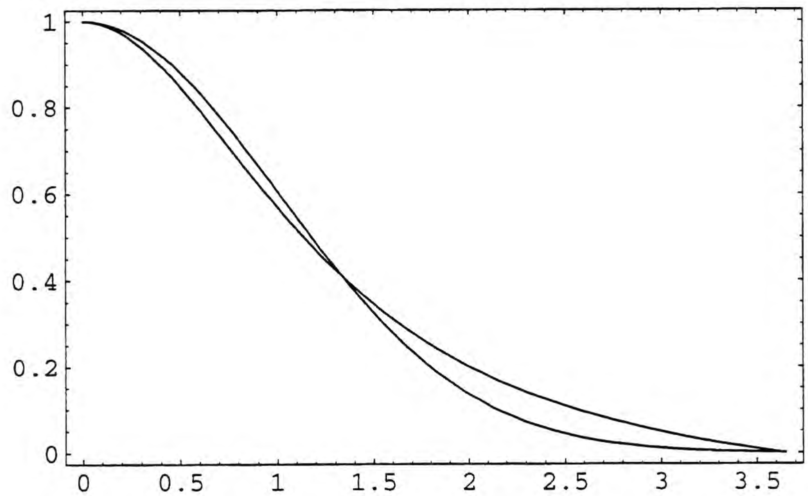

Figure 2. Left and right hand sides of the approximation (3.19).

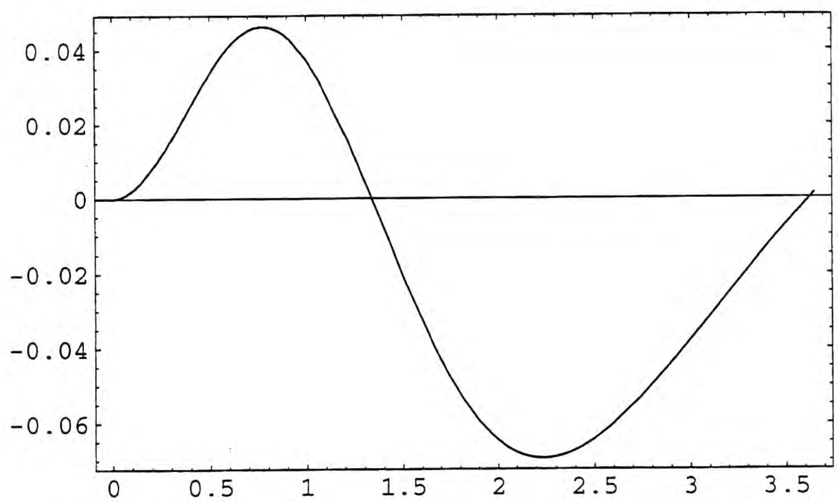

Figure 3. Plot of the approximation error $e^{-x^2/2} - \frac{1-0.075\ x^2}{1+0.625\ x^2}$.

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